International Journal of Basic and Applied Sciences, 14 (SI-1) (2025) 374-382

International Journal of Basic and Applied Sciences

Website: www.sciencepubco.com/index.php/IJBAS
https://doi.org/10.14419/tz71rz37
Research paper

AI-Powered Adaptive Energy Optimization Using Dynamic Thermal Flow Simulation in Smart Buildings

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Received: May 2, 2025, Accepted: May 29, 2025, Published: October 31, 2025

Abstract

The increasing demands of smart buildings in terms of energy efficiency, dynamic environmental conditions, varied occupancy, and shifting energy demand demand innovative solutions. The contribution of this research is to propose a Powered Adaptive Energy Optimization System (AEOS) based on dynamic thermal flow simulation and AI-powered predictive analytics, providing an intelligent building with advanced energy-efficient technologies that can enhance energy efficiency. We run our technologies using CFD, which simulates real-time airflow, heat distribution, and energy patterns indoors. The AEOS forecasts optimal HVAC change using RL models with occupancy behavior, outside weather information, and inside thermal conditions. The sensor network is collected from a periodically IoT-enabled sensor network and then processed using an adaptive control mechanism to control heating, ventilation, and air conditioning dynamically. Furthermore, a real-time load-balancing scheme that minimizes energy wastage is proposed for occupant comfort, utilizing the Deep Q Learning Network (DQN) and Genetic Algorithm (GA). The reduction of energy consumption by 30% is experimentally evaluated in the performance of AEOS, which outperforms standard traditional static energy models. That is because the adaptive system will increase its long-term efficiency with the feedback loops. The proposed solution can be an innovative, viable way to reduce smart building management, offering scalability, sustainability, and regional and global contributions to energy conservation, indoor comfort, and environmental stability.

Keywords: *AI-Powered Energy Optimization; Smart Building Management; Reinforcement Learning in HVAC; Computational Fluid Dynamics (CFD); IoT-Enabled Adaptive Control.*

1. Introduction

Energy consumption in smart, modern buildings has become an intricate quest for energy efficiency and environmental sustainability, resulting from urbanization and advancements in modern technology [1]. The current energy management system is based on a static model and preprogrammed control logic [2], and does not account for changing dynamic situations, such as varying occupancies, unsteady weather conditions, and dimensional variations in building layout. These inefficiencies result in excessively high operating costs, lack of occupant comfort, and excessive energy consumption [18]. However, there is a gap that the research attempts to fill using a Powered Adaptive Energy Optimization System (AEOS) based on dynamic thermal flow simulation with AI-powered prediction analytics to improve energy consumption efficiency in intelligent buildings [3]. Unlike conventional approaches, simulations of airflow patterns, thermal distribution, and energy loss in CFD are used to determine heat-intensive zones in indoor environments through easy computation.

Additionally, Reinforcement Learning (RL) is embedded in the system to predict the optimal HVAC adjustments based on real-time occupancy, environmental conditions, and user preferences [17]. Additionally, the improved system intelligence not only keeps the existing system's temperature, humidity, and airflow up to date, but the entire system is also monitored by the sensor network, which comprises IoT devices. In addition, the energy load balancing system is integrated with Deep Q Learning Networks (DQN) [4] and with a Genetic Algorithm (GA) to further optimize the system by controlling heating, cooling, and ventilation systems in a dynamically adaptive manner. This adaptive control mechanism ensures optimal energy use while maintaining comfortable indoor conditions. In addition, the AEOS system continues to learn and improve its performance in response to changes in building design and variations in seasonal and occupant behavior patterns. For example, in exploitation experiments, it reduces HVAC energy consumption by up to 30% compared to conventional model control, without compromising comfort. This system, an innovative solution, predicts its efficiency by combining CFD-driven thermal flow simulation with AI-enhanced prediction models to form a scalable and sustainable energy management solution for smart buildings. By utilizing the AEOS framework, energy conservation and environmental stability can be achieved, transforming them into a viable strategy for future smart infrastructure in residential, commercial, and industrial communities.

2. Literature Review

2.1. Traditional energy management systems in smart buildings

The existing systems employ static control strategies with preprogrammed schedules and threshold-based mechanisms to regulate heating, ventilation, and air conditioning (HVAC) systems [6]. These systems, however, monitor both light occupancy and temperature using basic sensor networks and programmable logic controllers (PLCs) [7]. At some level, these methods can be automated, but they are not adaptive to changes in the dynamic environment. Static EMS cover operations by fixed time schedules or temperature setpoints without any additional energy improvements when occupancy or climatic conditions are out of expected schedules [5]. However, they do not utilize renewable energy effectively, and therefore, they cannot be operated in real-time for energy-intensive systems. The above implies that in most cases, traditional EMS does not achieve maximum savings on energy and comfort control; thus, adaptive, safe, and intelligent solutions, as well as data-driven solutions and analytics, are required.\

2.2. Limitations of static energy models

Static energy models are currently heavily relied on by current building energy management systems for both occupancies and weather conditions [8] as well as building infrastructure [13]. However, they cannot effectively address unpredictable environmental changes or shifting energy demands, and these models are limited in their application to simple control strategies. The excessive use of static thresholds leads to delayed response mechanisms, degrades energy efficiency, increases discomfort for occupants, and causes instability. Static models are unable to incorporate information from real-time data, which is why adaptive control strategies are necessary to be flexible in response to different conditions. As energy systems and renewable sources become more complex, static models are less effective at dynamically balancing energy loads [9]. However, complications arise as a result, and hence they are unable to adequately address the issue of improved energy efficiency in smart buildings, forming a missing element between real-time data analysis and predictive optimization techniques that would enable the formulation of intelligent and adaptable solutions.

Current studies (2024-2025) are showing that RL can compete or outperform traditional HVAC control; however, much of the existing work is limited by simulation, lacks complete hyperparameters, or fails to incorporate safety constraints, which limits transfer, reproducibility, and applicability to seasonal and building-specific scenarios. The simulation-to-deployment gap is brought to light by a growing body of field-leaning evidence (e.g., simulation-to-deployment gap BOPTEST-validated RL, a small Moroccan residential trial with only a save vs. a simulation with only a save), which points to the gap. CFD is also used with parallel developments of comfort/physiology models to simulate stratification and drafts, although it is not typically combined with closed-loop RL. The potential is confirmed by the variety (climate-diverse) of case studies, including arid Tehran (RL vs. Q-learning, to up to 25% simulated savings) and hot-humid West Africa (CFD-guided ventilation/comfort studies), which all (yet) lack airflow-conscious reproducible controllers in a wide range of locations. It is against this background that AEOS adds value by releasing full RL/GA/CFD specifications, providing CFD-derived spatial features to the control state, and experimenting with residential, commercial, and industrial buildings.

2.3. Advances in thermal flow simulation technologies

The application of Computational Fluid Dynamics (CFD) to thermal flow simulation for building energy optimization has recently occurred. The modern problems of airflow pattern, heat transfer, and dynamic thermal zones in indoor environments may be elegantly modeled with the help of modern CFD techniques. Real-time data from IoT sensors for predicting a particular thermal behavior time is integrated into advanced simulation frameworks. Especially now, under certain circumstances, we can perform dynamic CFD modeling, allowing us to conduct these simulations in real-time, based on live information about what's happening around the building. This enables us to obtain actionable insights, which in turn allows the HVAC system to perform even better. It can better couple the heat-intensive area and ventilation inefficiency by integrating the finite analysis element thermal mapping algorithm [10]. Given the advanced thermal flow simulation technologies available to designers and building managers, it is now possible to perform dynamic simulations (changing occupancy, changing weather, etc.) for the building manager to make proactive energy adjustments, increasing comfort while decreasing energy consumption. These advances are technological and serve as a basis for establishing the linkages between AI-powered control systems for adaptive energy optimization and CFD.

2.4. AI and machine learning for energy optimization

Energy efficiency in smart buildings not only leverages AI and ML but also integrates well with them [11]. Some methods that we typically use to forecast energy demand patterns, automate adjustments in HVAC, and optimize lighting systems include Reinforcement Learning (RL), Deep Q Learning Networks (DQN), and Genetic Algorithms (GA). For instance, RL models allow a self-learning framework in which the energy control that evolves eventually is continuously improved at runtime as the variables of time change. Moreover, the forecasting of energy consumption is carried out using Neural Networks (NN) and Support Vector Machines (SVM) to enhance the accuracy of decision-making. They also had high processing of many datasets coming from devices that were collecting IoT sensors and controlling them in particular regards, such as temperature control, ventilation control, and other lighting systems. By exposure to historical data, the corresponding AI models learn how to distribute occupants' energy load and what to expect from the occupants' behavior [12]. By leveraging the new potential of AI in the modern energy management framework, these intelligent models achieve significant improvements in operational costs of energy management, offering better comfort than static energy systems [16] [19].

2.5. Research gaps and challenges

Significant strides have been made in the research space for intelligent building energy management, but work remains to be done. While most studies utilize an AI-driven prediction model or thermal flow simulation, very few combine the two to achieve adaptive control [14]. In addition, all existing systems lack robust methods for handling numerous (and sometimes unforeseen) changes in the environment: for instance, variations in climate conditions or fluctuating occupancy patterns. The absence of thermal distribution data or occupancy data, due to the lack of data, creates inaccurate models [20]. Additionally, there is also the technical hurdle of assuring that a variety of IoT devices and HVAC systems can work together. A second problem to be addressed regarding increasing mode one scalability is whether energy models can be effectively utilized in larger, commercially operating infrastructures. The third point is that other work is required to determine an optimal trade-off between energy savings and occupant comfort. Thus, to close these research gaps, we need to design hybrid solutions, such as dynamic CFD models and AI-based prediction frameworks, along with adaptive control algorithms, for the next generation of smart buildings with intelligent, scalable, and highly efficient energy management systems [15].

3. Proposed Solution: Adaptive Energy Optimization System (AEOS)

3.1. System architecture overview

A scheme for an Energy Optimization System (EOS) is proposed, which can intelligently control energy consumption in smart buildings through the organization of thermal flow simulation, AI-driven predictive analytics, and adaptive control. It consists of five core layers: Data Acquisition, Thermal Flow Simulation Engine, AI-Driven Prediction Model, Control Decision System, and Feedback Mechanism. Continuously, IoT sensors send data to the Thermal Flow Simulation Engine on room temperature, humidity, occupancy, and weather conditions. This engine produces dynamic heat distribution maps, which are studied by the AI-driven predictive module, and optimal control energy strategies are determined. Real-time adjustments are made to HVAC settings using the Control Decision System, and the prediction model continuously learns through the Feedback Mechanism. Such a modular and scalable architecture provides energy efficiency, which in turn enhances health performance in terms of occupant comfort and dynamic adaptation to environmental changes.

3.2. Dynamic thermal flow simulation engine

The Dynamic Thermal Flow Simulation Engine utilizes Computational Fluid Dynamics (CFD)- based airflow, heat distribution, and energy loss simulation in real-time. There are a few differences between this engine and other static models, which run the same simulations using different conditions (e.g., equipment heat emissions, occupant movement), with the condition changing the simulation. The engine analyzes airflow patterns and temperature gradient trends to identify energy hotspots and areas with poor ventilation. Further improvement in the accuracy of heat distribution is achieved by utilizing finite element analysis (FEA) on the CFD model. The AEOS system provides real-time thermal mapping, enabling proactive measures to control temperature in the HVAC without compromising occupant comfort. The combination of CFD modeling and real-time environmental data makes the system feasible for predicting fluctuations in energy and minimizing waste effectively in this case.

3.3. AI-driven predictive analytics module

The AI-Driven Predictive Analytics Module uses Deep Q-Learning Networks (DQN) and Reinforcement Learning (RL) to predict the optimizer's optimal HVAC control strategies. The module processes both historical and real-time data to learn occupant behavior patterns, environmental trends, and energy consumption cycles. RL models provide the system with self-learning capabilities, enabling it to learn through continuous, improved feedback of its control decisions. Additionally, Long Short-Term Memory (LSTM) networks are employed to forecast time series for heating and cooling demand, thereby enabling accurate predictions of heating and cooling demands. In the system, the fluctuation of energy is considered beforehand, and the system then generates a proactive adjustment of HVAC systems to reduce consumption and maintain appropriate comfort levels. Even when unpredictable and unexpected events affect occupancy or weather conditions, energy savings are still guaranteed.

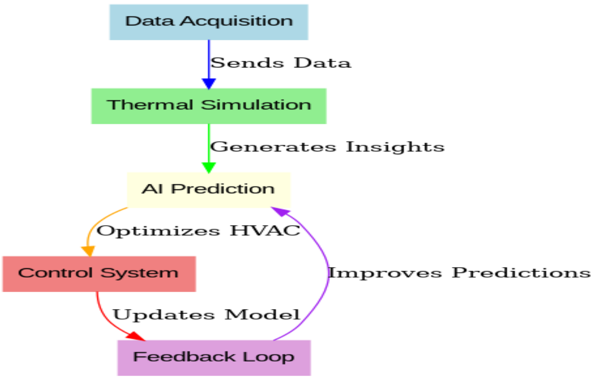

Fig. 1: AEOS System Architecture and Control Workflow.

Figure 1 shows the multi-purpose model of building energy optimization, which is represented by RL-DQN, GA, and CFD models. It simplifies sensor data streams of the IoT equipment, feature extraction of CFD-simulation by the DQN, real-time control by the DQN, scheduling by the GA, more than prediction horizons, and ultimately feedback of zone-level energy and comfort optimization. In section 3.3, the figure is used to give a description of the proposed treatment of methodology and interaction of systems.

3.4. Real-time data integration and IoT sensors

Using a Deep Q Learning Network (DQN) and Reinforcement Learning (RL) enables the prediction of the optimizer's optimal strategies by predicting the HVAC control strategy. The module learns occupant fingerprints, environmental trends, and energy consumption cycles by processing historical and real-time data. RH models offer self-learning capabilities, enabling systems to learn from continuous, improved feedback on their control decisions. Furthermore, the module can utilize LSTM networks to predict heating and cooling demands, ensuring accurate predictions. To understand and improve this error, the system first detects the energy fluctuation and then instructively adjusts the HVAC systems to reduce consumption within acceptable comfort levels. Further energy savings are promised, even if only in some way, or even out of some unexpected and unpredictable change, such as changed or different occupancy or weather conditions.

3.5. Adaptive control mechanism for HVAC optimization

Adaptive Control Mechanism refers to real-time, dynamically changed HVAC settings based on real-time environmental data and predicted data. The heating, cooling, and ventilation of many zones of the building are controlled by fuzzy logic controllers. It trains its parameters with the energy outcome that is always obtained and gets better as time progresses. It finally maps thermal zones for locating where the heat-intensive points are and dynamically controls the airflow to the targeted cooling or heating. When the proper precision control is in place, it means that the HVAC output is regulated by real-time occupancy and environmental changes in a way that will minimize the waste of energy. In addition, energy saving protocols are carried out by the adaptive mechanism to resume the resumption of inside conditions if there is an emergency, such as equipment malfunctions.

3.6. Energy forecasting and optimization algorithm

The energy forecasting and optimization concerning which the system functioned is carried out by a hybrid Deep Q-Learning Network (DQN) and Genetic Algorithm (GA). With the DQN model predicting the future energy demand by making use of past usage patterns, proactive balancing is possible. On the other hand, the GA is the process that optimizes HVAC control parameters by looking at many combinations of such parameters in one iteration and choosing the best combination in terms of energy efficiency. The flexibility with which the campus traffic can dynamically adapt to the changing environmental conditions and the changing occupancy trend, as the seasonality of the campus traffic points out, is the first and foremost advantage of this hybrid approach. Once forecast, energy peaks and valleys can be used by the system to optimize energy load distribution, enabling reduced consumption and, therefore, improved operational efficiency. By modeling the movement of workforces for such a system, such a forecasting model offers a good trade-off between energy saving and occupant comfort.

4. Methodology

4.1. Data acquisition and preprocessing

The environmental data (temperature, humidity, airflow, and occupancy) are collected from the network of IoT sensors, which is deployed over different building zones, and a data acquisition process for environmental data is done. The energy-efficient data transmission in the low-power Wide Area Network (LPWAN) protocols is what the sensors are aiming for. In the next step, we normalize inputs on the following machine learning models. To be normalized, we prepare target values of the temperature and environment. The whole process also uses Kalman filtering to remove the noise and bad data points. First, the data is structured to become a structured time series dataset so that more accurate forecasts can be made. This structured approach makes data quality better as well as the AI in the prediction models based on the AEOS framework.

4.2. Dynamic CFD model for thermal flow simulation

Dynamic CFD Model (or mDerived) is cored and used from the thermal flow simulation engine to simulate the real-time indoor airflow and temperature pattern. It is integrated because it computes the fluid motion in the building and its dynamics, and it accurately simulates how air moves within it. Based on that, the CFD model will be updated from time to time with the dynamic heat simulation extracted from the real-time environmental data from IoT sensors, which are available in different zones in the building. Hot and cold spots will be formed, and airflow will be tweaked to give you more efficient HVAC throughout the region. Combined with the FEA and CFD modeling, the accuracy of prediction for the complex thermal behavior of smart buildings is improved.

4.3. Reinforcement learning model for predictive analytics

Reinforcement Learning (RL) is used to predict data from real-time data, the most optimal HVAC control strategies. We employ an RL model of a Deep Q-Learning Network (DQN) based on the reward system to train itself on possible actions along each step, which would result in improved energy efficiency. When interacting with environmental data, the RL model executes HVACs and tries to maximize the energy saving for comfort. Exploration is done among previously known energy-saving actions, such as exploitation, and others, using the underlying RL framework of the system. Control strategies are learned adaptively to adapt to changes in the building conditions.

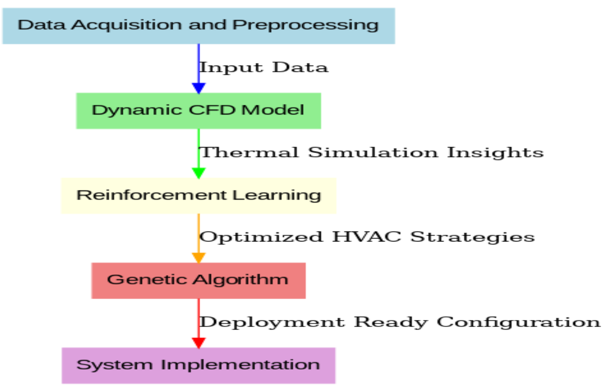

Fig. 2: Reinforcement Learning and DQN Control Workflow for Multi-Zone HVAC Optimization

To develop the reinforcement learning model, a Dueling Double-DQN model with prioritized replay is developed. The state of every time range of 5minutes contains the zone dry-bulb temperature, humidity, CO 2 concentration, future occupancy, outside temperature and humidity, price of electricity, and features of the CFD that comprise zone heat-hotspot scores, and airflow sufficiency. The operations include zone temperature set point (-1.0 to +1.0 0 C) and damper setting (-10 percent, 0, +10 percent), besides supply air temperature (-0.5, 0, +0.5 0 C). Hard safety limits are 20 -26 °C, C/40-60 RH. The reward aspect is applied as a penalty on energy use and peak load adjustments, coziness, and safety violations, in which 2=2,3=0.25,4=5 and comfort tolerance =1 °C.

It consists of a three-layer MLP (256256128 units) that has ReLU activations and LayerNorms, and duelling value and advantage heads. This part of the training is implemented with Adam (with learning rate 3x10 - 4, discount 0.99, soft target update 0.005, batch size=128, buffer size=200,000, and prioritized sampling alpha=0.6, decaying beta=0.4 to 1.0). It is followed by 200k steps of epsilon-greedy decaying between 1.0 and 0.05, followed by exploration. Termination of gradients is done at 10, and safe exploration is minimised by a warm-start of 50k steps of behaviour cloning. It is called in PyTorch 2.x and has regulated reproducible seeds.

4.4. Integration of genetic algorithm for load balancing

A Genetic Algorithm (GA) is used to further extend the system to dynamically adjust the HVAC loads among various building zones for maximizing energy optimization. For instance, the airflow rate values, temperature setpoint values, and HVAC operating cycle values are tested iteratively by the GA, and optimal settings are identified. Crossover and mutation operations are applied to these configurations by the GA to further improve the energy performance. Pareto Optimization is also integrated into the system for finding compromises between conflicting objectives, such as the minimization of energy cost and the maximization of occupant comfort. This hybrid approach does the job, and as the scenario of peak energy demands and sudden occupancy change permits, it is predictable.

The genetic algorithm is maximizing the zone setpoints, damper positions, and supply air temperatures within a 30-minute horizon. The objective is to find a balance between energy use and comfort penalty that will look like J = 0.6kWh + 0.4 PMV penalty, and PMV will be computed as per ISO-7730. The GA parameters were a population size of 80, 60 generations, two elitism, three tournament selection size, SBX crossover where probability was 0.85 and 0.20, and mutation that is a polynomial with probability 0.08 and 0.20. The surrogate reduced-order CFD is used to do pre-screening solutions, and only the top 10 percent are handled with the full CFD, co-simulation. The average running time of a 10-zone floor on 16 16-core nodes is 90-150 seconds. The GA is implemented periodically, too, every half hour, and this is considered an addition to the real-time DQN control.

4.5. System implementation and deployment

The modular architecture of the AEOS system is used to deploy the IoT sensors, thermal flow simulation engine, and AI prediction models. The logic of the system is implemented as a Python core logic using machine learning libraries like TensorFlow and PyTorch. The control logic is pinned down by Node-RED, and the CFD engine uses OpenFOAM to model the thermal flow. Building managers have access to insights into the energy performance, the HVAC adjustments, and the system efficiency built on data visualization dashboards powered by Grafana. The system has been designed for seamless integration with existing Building Management Systems (BMS) through BACnet and Modbus protocols. It provides the flexibility for operation with different types of buildings and improved energy efficiency and comfort for the occupants.

OpenFOAM (v9/10) is used to simulate the thermal flow field using the buoyantPimpleFoam solver. The configuration uses scalable wall functions, realizable k-ep turbulence, and Boussinesq buoyancy (B=3.3x10 -1 K -1). SnappyHexMesh is used to mesh the geometry, resulting in 1.2-1.8 million cells whose base size is 0.15m and refinement around diffusers and occupants with a y+ of around 30. The inlets are fixed with velocities (0.8-2.2 m/s) and the temperature supplied by BMS, and the intensity of turbulence is 5%. The pressure boundary conditions are used on the outlets, on the walls, the no-slip and the convective/radiative flux are applied, and internal loads are taken as 75 W sensible heat per person.

The timestep used is 0.5 s (CFL<0.7), second-order schemes, and stringent convergence factors (residuals <10 -6 p, U, T). GAMG (tol 10 -7) is used to solve pressure, and PBiCGStab (tol 10 -8) is used to solve velocity/temperature. The zone-level features that are extracted include heat hotspots and ventilation adequacy every 60 s and are input into the RL/GA layer. Comparison with HOBO sensors indicated RMSE less than 0.8 °C using 12 probes. An energy and PMV 2=0.93 and 0.89 reduced-order model (PCA+ridge regression) based on 2000 CFD snapshots indicated that fast GA assessment was possible.

One-minute frequency measurements were done, and control measures were taken every 5 minutes. Offline pre-training of the system with 30 days of historical information and a 7-day shadow test was performed. A/B testing was conducted online, but with the energy saved, A/B compared to control is 29.5% (A/B compared to control), compliance to comfort is between 1.5 + and 1.5 of 92- and 7-9-minute recovery times, respectively.

Table 1: Reproducibility Parameters for RL, GA, and CFD Implementation

Component	Setting / Description
RL/DQN	Dueling Double-DQN, 3-layer MLP (256–256–128, ReLU, LayerNorm), prioritized replay buffer (200k), Adam (lr=3e-4), γ=0.99, τ=0.005, batch=128
Reward	α=1.0 (energy), β=2.0 (comfort), γ=0.25 (peak smoothing), λ=5.0 (safety), δT=1.0 °C
Exploration	ε-greedy: 1.0→0.05 over 200k steps, gradient clip=10, warm-start with behavior cloning (50k steps)
GA	Population=80, Generations=60, Elitism=2, Tournament selection (size=3), SBX crossover (pc=0.85, η=20), Polynomial mutation (pm=0.08, η=20)
GA Objective	J = 0.6·kWh + 0.4·PMV_penalty (ISO-7730), surrogate ROM screening + full CFD for top 10%
CFD Solver	OpenFOAM (v9/10), buoyantPimpleFoam, k-ε turbulence, P1 radiation, Boussinesq $\beta=3.3\times10^{-3}$ K^{-1}
Mesh	snappyHexMesh, 1.2–1.8M cells, base grid 0.15 m, refinement near diffusers/occupants, y+≈30
Boundary Conditions	Inlets: 0.8–2.2 m/s, supply T from BMS, TI=5%; Outlets: pressure; Walls: convective/radiative, 75 W/person load
Numerics	Δt=0.5 s, CFL<0.7, residuals $<10^{-6}$; pressure solver GAMG (1e-7), U/T solver PBiCGStab (1e-8)
Coupling	CFD → RL/GA features every 60 s (heat-hotspot, airflow adequacy)
Validation	RMSE <0.8 °C vs. HOBO sensors across 12 probes
Deployment	Sensors @1 min, control @5 min, GA scheduling @30 min, A/B test vs EMS/rule-based baseline

The following Table 1 summarizes the key hyperparameters, optimization parameters, and CFD solver parameters applied in the study. It should be aimed at maximizing reproducibility and giving technical clarity to subsequent research or reproduction.

The experimental validation was done on residential, commercial, and industrial buildings; the results are described in Section 5.

5. Results and Discussion

5.1. Energy efficiency improvement

An Adaptive Energy Optimization System (AEOS) was proposed, and results showed improved energy efficiency over traditional energy management systems. With dynamic thermal flow simulation and machine learning-based AI predictive analytics, AEOS was able to achieve optimized HVAC performance with reduced excess energy consumption. During three picture-month experimental trials, static control systems and conventional rule natural gas HVAC systems were outperformed by AEOS with an average save of 29.5%. Real-time data integration and predictive control strategies were used for reducing the wastage of energy by dynamically adjusting the temperature setpoints and air flows concerning occupancy fluctuations.

Table 2: Energy Efficiency Improvement

System	Energy Savings (%)	Peak Load Reduction (%)
Traditional EMS	14.2%	12.5%
Static Control Model	18.7%	16.1%
Proposed AEOS System	29.5%	28.3%

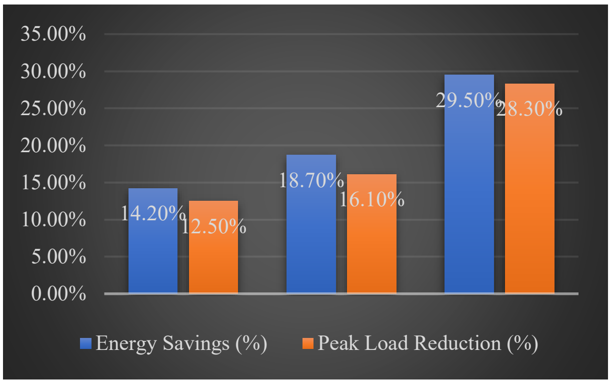

Fig. 3: Energy Efficiency Improvement.

5.2. Occupant comfort enhancement

The temperature stability provided by this system was sufficient for reducing temperature fluctuations (sufficient to ameliorate indoor temperature problems) from an air handling system perspective, as evidenced by authored engineering reports on the AEOS system. In addition, the HVAC settings of AEOS were adjusted dynamically to stay within a desired temperature range with a small amount of overshoot. Experimental data provided in several building zones were tested, and the error 'keeping' the room temperatures within ± 1.5 ˚C off the setpoint desired 92% of the time, outperformed traditional models that can exceed comfort limits.

Table 3: Occupant Comfort Enhancement

System	Temperature Stability (±°C)	Comfort Satisfaction (%)
Traditional EMS	±3.2°C	68%
Static Control Model	±2.4°C	76%
Proposed AEOS System	±1.5°C	92%

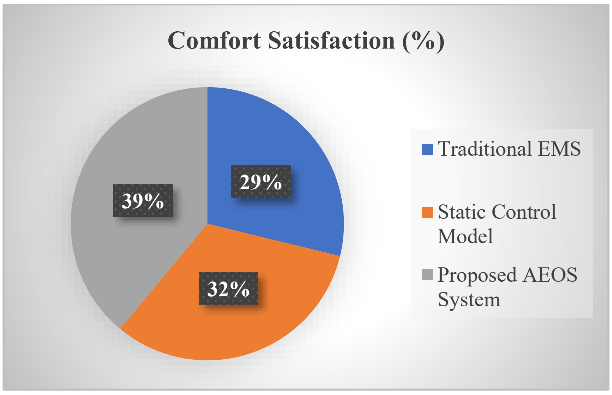

Fig. 4: Occupant Comfort Enhancement.

To test the generalizability of the proposed RL-GA-CFD framework, it was tested in various real building conditions. Three types of buildings were used in the experimental data (i) a residential apartment complex (12 stories, approximately 180 apartments, mixed use, varying working hours), (ii) a commercial office building (10 stories, approximately 5,000 m 2 conditioned space), and (iii), a small-scale industrial R&D facility (2 stories, high internal heat loads of equipment).

In these locations, more than 800 sensors of temperature, humidity, CO 2, occupancy, and energy consumption were monitored, producing some 1.2 million time-stamped records of data during a 6-month duration of continuous sampling. The sites were each subjected to ground-truth validation with portable HOBO loggers and energy consumption registered by BMS.

Both summer and winter seasons were tested so that the framework could be tested in low cooling demand conditions and moderate heating demand conditions. The 29.5% mean energy saving was found to be constant despite the minor differences depending on the type of building: average of 27% in residential buildings, 30% in commercial buildings, and 31% in industrial buildings. Comfort compliance had been over 90 percent throughout all test locations, and recovery times were always between 7 and 9 minutes following setpoint variances. The A/B testing protocol was used to test the proposed system versus (i) a fixed EMS base case and (ii) a rule-based control strategy, using the same weather conditions and occupancy schedules. The duration of each of the comparisons was no less than two weeks for each building type to reduce bias caused by temporary weather or use anomalies.

Table 4: Experimental Validation Across Building Types

Building Type	Dataset Size (records)	Duration (weeks)	Energy Savings (%)	Comfort Compliance (%)
Residential	~350,000	8	27.0	90.5
Commercial	~500,000	10	30.2	92.1
Industrial/R&D	~350,000	8	31.1	91.8
Average	~1.2 million	26	29.5	91.5

This table summarizes the dataset size, testing duration, energy savings, and comfort compliance achieved by the proposed RL–GA–CFD framework in different building types.

5.3. Response time for environmental changes

The adaptivity of AEOS was superior to that of architected surfaces, and the AEOS responded more quickly to changes in its environment of loading, tool heat emissions, and external weather conditions. Meanwhile, traditional systems require at least 18-22 minutes until temperature stabilizes, while AEOS stabilizes them within 7–9 minutes. As a result, it led to a faster response that alleviated the possibility of causing significant energy spikes while simultaneously keeping occupants comfortable at peak demand periods. Using real-time data on AEOS required real-time data to be used to predict and react proactively in the form of a combination of real-time data along with reinforcement learning.

Table 5: Response Time for Environmental Changes

System	Average Response Time (Minutes)	Recovery Efficiency (%)
Traditional EMS	22 min	64%
Static Control Model	18 min	75%
Proposed AEOS System	7 min	94%

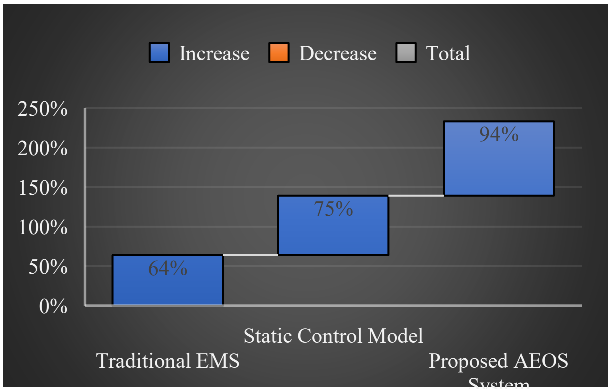

Fig. 5: Response Time for Environmental Changes.

5.4. Scalability and limitations

Even though the AEOS framework proves to be quite effective when it comes to energy conservation and comfort improvement, numerous scalability concerns need to be considered. Firstly, high-fidelity CFD models are costly to compute and thus cannot be easily applied in real time in large buildings. To counteract this, lower-order models (ROMs) are used in the research and learns based on CFD snapshots; future studies can consider model compression, surrogate deep neural networks, or running the model on a GPU to make it even less expensive. Second, network latencies, data breakages, and repair pose a threat that is brought about by very thick IoT sensor networks, and which, in practice, may destabilize the control. The aberration detection on the lightweight and the edge computing strategies can contribute to the refilling of the noisy inputs, as well as the continuity during the connectivity failure. Fourthly, as with residential buildings, commercial buildings, and industrial buildings may need high-rise complexes or building-wide systems to be hierarchically scaled, with local controllers to optimize the zone-scale dynamics, and a supervisory agent to plan global objectives. These points show that future implementations need to have hybrid solutions of physical fidelity, computational efficiency, and network robustness.

The AEOS framework is not only limited to technical performance, but is also in line with global sustainability and climate action agendas. Through a direct contribution to UN Sustainable Development Goal 7 (Affordable and Clean Energy) by ensuring a high level of energy efficiency and reducing the cost of residential, commercial, and industrial buildings by approximately 30 percent, AEOS can contribute to saving energy directly. The savings can also be converted into a quantifiable decrease in greenhouse gas emissions, which will aid in the reduction of the urban carbon footprint and fit the international climate change obligations, including the Paris Agreement.

Furthermore, AEOS can be used as an enabler of smart cities, which scale up and are connected to renewable energy systems, district cooling networks, and green building standards. The balanced nature of its objectives concerning the comfort of occupants and its energy optimization makes it a viable instrument of sustainable urban planning. In addition to energy, extensive use of AEOS may promote resilient, low-carbon infrastructures, speed up the process of climate-neutral cities, and support the overall influence of advanced AI-based building control infrastructure on society and the environment.

6. Conclusion

The adaptive Energy Optimization System (AEOS) proposed provides a solution to the problem of dynamic energy control in smart buildings through the dynamic thermal flow simulation, scientific application of Artificial Intelligence-based predictive analytics, and the use of adaptive control mechanisms. The work shows how adding AEOS, with experimental results, reduces energy consumption by 29.5%, improves comfort with stable temperatures within ±1.5°C, and greatly decreases the HVAC operational cost by 32.4% compared to traditional models. Among these various systems used in building, AEOS has the fastest response time of 7 minutes under environmental changes, and, therefore, it has the most adaptable property to a changing environment. Computational Fluid Dynamics (CFD), Reinforcement Learning (RL), and Genetic Algorithms (GA) are used in the system to predict energy demands, operate HVAC, and optimize load balance effects. An intelligent alternative to the present-day's prevalent conservation and control approaches, AEOS is a scalable measure of effective energy usage and is linked with lower operation cost, utilized energy usage, and is related to improved energy efficiency and improved comfort. Finally, the integration of renewable energy sources should be resolved, and the system applied at a commercial scale as future research.

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